Science Education
Review Letters

Covariates of complex problem solving competency in chemistry

Ronny Scherer*[a], Kerstin Patzwaldt[a], Rüdiger Tiemann[a]
[a] Humboldt-Universität zu Berlin, Department of Chemistry, Chemistry Education
*Corresponding author: ronny.scherer@chemie.hu-berlin.de

Received 7th July 2011, Accepted 25th August 2011

Abstract
The ability to solve complex and real-life problems is one of the key competencies in science education. Different studies analyzed the relationships between complex problem solving (CPS) and covariates such as intelligence, prior knowledge, and motivational constructs on a manifest level. Additionally, research findings indicate that intelligence and prior knowledge are substantial predictors of CPS. Due to the interconnections between covariates, the relationships between CPS and covariates are quite complex. Therefore, we propose a model which describes these relations by taking direct and indirect effects into account. All analyses are based on structural equation modeling.
Results show that the proposed model represents the data with substantial goodness-of-fit statistics and explanation of variance. Intelligence, domain-specific prior knowledge, computer familiarity, and attendance in advanced chemistry courses are direct predictors of CPS, while interest and scientific self-concept show indirect effects.

Keywords
Chemistry Education; Complex Problem Solving; Computer-Based Assessment; Structural Equation Modeling; Virtual Environment

1. Introduction and theoretical background

Complex problem solving (CPS) can be regarded as one of the key competencies in science education and includes scientific inquiry (Funke & Frensch, 2007; OECD, 2010).
Current research focuses on assessment procedures of CPS, which contain complex and dynamic problems requiring an interaction between the problem solver and the system in order to obtain information about the system and its variables. In contrast to analytical or static problem solving, the information which is necessary for the problem solution is not given at the beginning of the problem solving process. Therefore, virtual micro-worlds or simulations are quite useful for the assessment of CPS (Leutner, 2002; Wirth & Klieme, 2004).
Herein, various cognitive variables are involved and determine the structure of CPS (Funke, 2010). Many researchers in science education proposed problem solving models, which could be adapted for CPS competencies by taking the interactive character of problem tasks into account (e.g., Cartrette & Bodner, 2010; Taasoobshirazi & Glynn, 2011). However, this study is based on a framework which was proposed by the OECD (2010) and adapted for the domain of chemistry by Koppelt (2011). In this model, CPS is operationalized by four distinct steps: (1) understanding and characterizing the problem (PUC), (2) representing the problem (PR), (3) solving the problem (PS), (4) reflecting and communicating the solution (SRC). These steps form the structure of CPS and are quite similar to the MicroDYN approach (exploring,

modeling, controlling), which was established by Greiff and Funke (2009).
Furthermore, researchers focused on the analysis of the relationships between CPS and covariates. In many studies, constructs such as intelligence, prior knowledge, motivation, self-concept, and computer familiarity were predictors of CPS performance (e.g., Bühner, Kröner & Ziegler, 2008; Funke & Frensch, 2007; Hambrick, 2005; Lee et al., 1996; Schoppek & Putz-Osterloh, 2003; Schroeders & Wilhelm, 2011). Additionally, Köller et al. (2006) argued that self-concept, school grades in prior classes, and the participation in advanced courses influenced performances in competence tests. They found indirect effects of participation in an advanced course and marks in grade 10 via self-concept. The influence of interest was statistically not significant.
A quite contradictory situation exists when it comes to the relationship between intelligence and CPS. There were different approaches to investigate whether or not CPS could be regarded as a sub-dimension of intelligence (Funke & Frensch, 2007). The correlations differed according to the factors the intelligence tests measured (Leutner, 2002). However, intelligence was a predictor of CPS.
Few studies described the relationships on a latent level by taking the interconnections between covariates into account. Therefore, we analyze the structure of relations with the help of latent models which account for structural relations.

2. Research questions

In this study, we focus on the complex relationships between CPS and covariates by taking direct and indirect effects into account. Based on empirical findings, the following constructs are analyzed: chemistry-specific complex problem solving competency (CPS) as the dependent variable, and covariates such as fluid intelligence, domain-specific prior knowledge, computer familiarity, interest and motivation in chemistry and natural sciences, participation in an advanced chemistry course, scientific self-concept, and marks in chemistry of the 10th grade. In order to minimize bias in parameter estimation, we analyze the structure of relationships between CPS and covariates by establishing a structural equation model.
Consequently, our research question is: Which relationships exist between CPS and covariates by taking the latent character of constructs into account, and by modeling the complex interconnections between covariates as well?

3. Methodology

3.1 Participants

N=149 students attending upper secondary chemistry courses of grades 11 to 13 in Berlin and Brandenburg (mean age: 17.40, SD=.92, Min=16, Max=22; male: 50.3%) worked on a computer-based test scenario of CPS and computerized versions of covariate tests in two sessions of 90 minutes each.

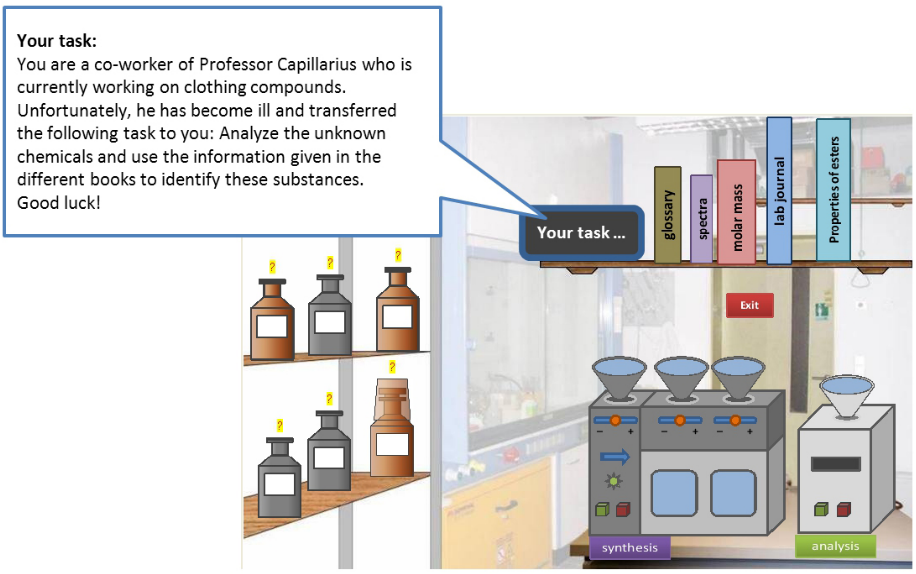

Fig. 1: Screenshot of the virtual laboratory

3.2 Measuring instruments

3.2.1 Complex problem solving competency

Based on the four-dimensional model of CPS, we developed a computer-based assessment tool for students of the upper secondary level. The test was implemented in a virtual laboratory with interactive and static features (figure 1).

After an exploration phase, students had to identify unknown chemicals by using at least one of two machines representing so-called "black boxes". The relationships between variables such as concentration, use of distillation and/or light were unknown at the beginning. While interacting with the virtual laboratory, functionalities of machines and the connectivity of variables became apparent. This phase was followed by the main task, in which students had to synthesize a polyester fiber. The required substance was unknown and had to meet given criteria. To further investigate CPS competencies (i.e., PUC, PR, PS, and SRC), additional items were administered. These items were implemented as static multiple-select tasks, in which students had to answer questions or complete concept maps. If students failed in one of the four steps, they would nevertheless be able to solve the task successfully. After completing these tasks, the students' answers and problem solving behavior were logged and evaluated by using a reliable coding scheme.

3.2.2 Covariates of CPS

Based on the results of previous studies, we assessed different covariates by using computerized versions of empirically validated tests. The following motivational constructs were taken from the PISA 2006 pupils' questionnaire (OECD, 2009): (a) three factors of interest in chemistry and science (*Interest*): general interest in chemistry (*IntChe*), enjoyment in science (*JOYSCIE*), and interest in natural sciences (*IntSCIE*), and (b) one factor of scientific self-concept (*SCSCIE*). Furthermore, computer familiarity was assessed (*CompFam*) by using four PISA subscales of the construct (OECD, 2009): computer usage of school and basic programs, computer-related control beliefs, and attitudes towards computers (*COMPUSE 4, 6, 8, 11*). In order to take the students' prior knowledge into account, a domain-specific knowledge test (*DSK*) was developed. Fluid intelligence (*Intelligence/Int*) was assessed by a cognitive ability test, in which students had to work on figural analogies (Heller & Perleth, 2000). Finally, we recorded the students' course participation at the upper secondary level (*ACChem*; 0=basic chemistry course, 1=advanced chemistry course), as well as their marks in chemistry at grade 10 (*GradeChe10*).

3.3 Procedure

In order to facilitate answering our research question, we established a structural equation model with CPS as a latent variable, indicated by four manifest scales which represent the students' performances in each of the problem solving steps (*PUCsum, PRsum, PSsum, SRCsum*). This procedure has the major advantage of correcting for measurement error within the relationships between constructs. The model was estimated with Mplus 6 (Muthén & Muthén, 2010), which uses the full-information-maximum-likelihood procedure to impute missing data on a model-based level. To further evaluate the model fit, we took different goodness-of-fit statistics such as the CFI, RMSEA, SRMR, and the χ^2-test into account (Marsh et al., 2005).

4. Results

4.1 Scaling outcomes

Due to missing values of the CPS data set, we determined the expected-a-posteriori/plausible (EAP/PV) reliability with *ACER ConQuest 2.0* (Wu et al., 2007) by applying a partial credit model. The EAP/PV value of .74 was sufficient for the computer-based assessment (83 items).

Furthermore, the covariate scales showed substantial reliabilities above .80, except for the domain-specific prior knowledge scale (DSK, see table). Cronbach's α for *DSK* was .65, which is low but acceptable for tests measuring multidimensional constructs in different content areas (Kalyuga, 2006). [See Tab. 1]

4.2 Structural equation modeling

The proposed structural equation model accounts for direct and indirect relationships between CPS and related constructs (see figure 2). The resulting goodness-of-fit statistics revealed an acceptable model fit (χ^2=225.55, df=178, $p<.01$, χ^2/df=1.27, N=149, CFI=.95, RMSEA=.05, $p_{(RMSEA \leq .05)}$=.50, SRMR=.09) with a substantial explanation of variance in CPS performance (R^2=.739). Herein, we found statistically significant and direct influences of computer familiarity (β=.337, $p<.01$), fluid intelligence (β=.524, $p<.01$), domain-specific prior knowledge (β=.467, $p<.01$), and participation in an advanced chemistry course (β=.214, $p<.05$) on CPS. Intelligence and prior knowledge were substantial predictors and explained approxi-

Tab. 1: Descriptive statistics and internal consistencies of covariate scales on a manifest level.

Scale	N_{Items}	N_{Sample}	*M*	*SD*	*Min*	*Max*	α
Interest	15	139	2.01	.53	.22	2.89	.90
SCSCIE	6	141	1.69	.65	.00	3.00	.90
CompFam	20	132	2.08	.41	1.00	2.91	.85
Intelligence	25	114	13.17	4.47	2.00	22.00	.82
DSK	17	149	15.23	4.21	0.00	23.00	.65

Note. N_{Items}=number of items, N_{Sample}=number of complete data sets, M=mean, SD=standard deviation, Min=minimum, Max=maximum, α is the value of Cronbach's α. Subscales of *Interest* and *CompFam* (computer familiarity) were combined.

mately 20% of variance in CPS. All path coefficients were below .60 and indicated low to medium effects.

In order to interpret the negative, statistically insignificant, and direct effect of *Interest* on CPS (β=-.440, n.s.), we analyzed whether or not confounding indirect effects existed which weakened this relationship. We found a low indirect effect of *Interest* on CPS mediated by domain-specific prior knowledge ($\beta_{indirect}$=.131, p<.05). But the total effect of *Interest* on CPS was statistically not significant (β_{total}=-.309, p=.29). Additionally, we found a significant but low indirect effect of SCSCIE on CPS mediated by *Interest* and prior knowledge (β=.106, p<.05).

Taken together, we found four substantial predictors of CPS performance with direct effects: computer familiarity, fluid intelligence, prior knowledge, and participation in an advanced

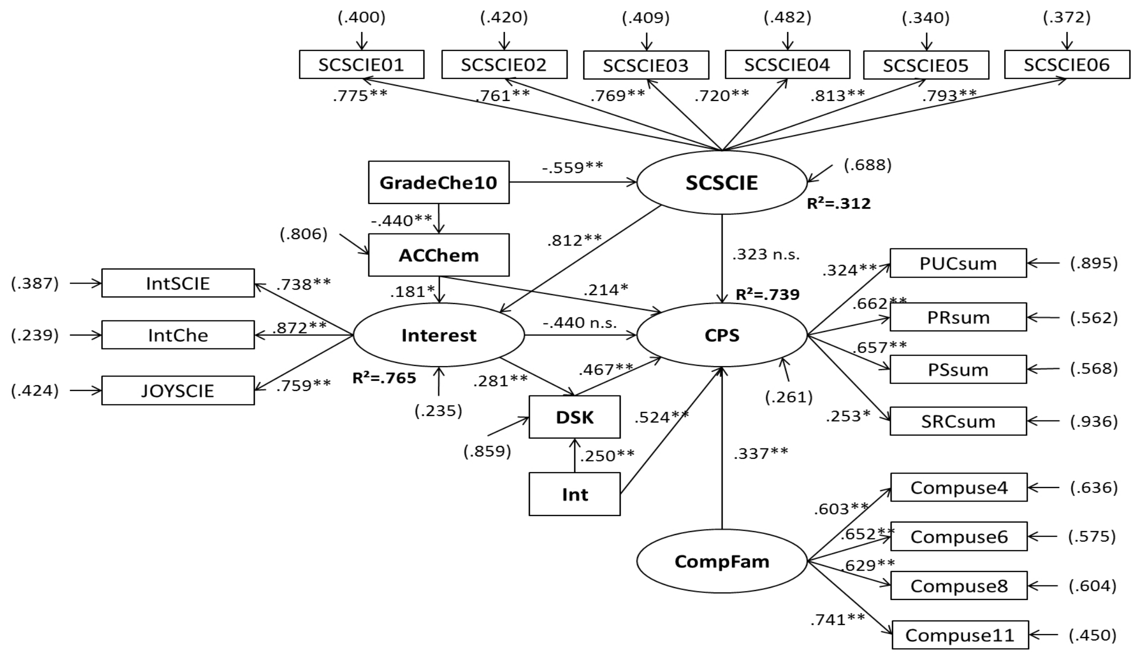

Fig. 2: Structural equation model of CPS and covariates (N=149)

Note. The figure contains the fully standardized values. All residual variances are statistically significant with p<.01 except for CPS (p<.05). R^2=explanation of variance, n.s.=statistically not significant, *p<.05, **p<.01.

chemistry course. Indirect effects via prior knowledge resulted with self-concept and interest.
In order to assess the influence of participation in advanced chemistry courses more precisely, we further conducted an ANOVA with CPS as the dependent variable. We found significant differences favoring students of advanced courses with a very low effect size (advanced: M=55.57, SD=22.77, N=101; basic: M=45.15, SD=20.12, N=47; $F(1,146)=7.89$, $p<.01$, $\eta^2=.051$). 5.1% of variance in CPS was explained by course participation.

5. Discussion

This study focused on the relationship between CPS and covariates. The resulting model of CPS and related constructs revealed acceptable goodness-of-fit statistics. Although the path coefficients of direct and indirect effects were lower than .60, the model explained over two thirds of variance in CPS. This finding indicates that CPS can be separated from related constructs such as domain-specific prior knowledge or fluid intelligence, and validates the CPS assessment procedure. Furthermore, it implies that CPS is not a construct which can be regarded as a composition of prior knowledge, intelligence, and personality characteristics but requires far more competency. Thus, our study replicates the results of previous studies which found direct influences of the covariates mentioned above (prior knowledge: Hambrick, 2005; intelligence: Leutner, 2002; personality characteristics: Funke & Frensch, 2007).
In detail, the influence of computer familiarity on CPS was expected due to the computer-based assessment procedure. Students who were familiar with complex computer procedures performed better in computerized tests (e.g., Schroeders & Wilhelm, 2010).
The indirect effect of interest on CPS, which is mediated by *DSK*, accounts for the domain-specificity of problem solving. Students who are interested in chemistry and natural sciences are willing to acquire and apply domain-specific knowledge, and, thus, show high scores on CPS.
It somehow shows that domain-specific CPS requires a certain level of prior knowledge which could be applied by focusing effort in problem solving tasks (e.g., Bryan, Glynn, & Kittleson, 2011; Koeppen et al., 2008). Herein, self-concept and interest are determining factors of a successful use of prior knowledge. It would be interesting to further investigate whether or not these relationships hold for general CPS.
The indirect effect of self-concept on CPS mediated by interest and prior knowledge can be interpreted in the same way by adding the finding of "a high self-concept leads to a greater interest in chemistry". Our results also confirm the results of Köller et al. (2006) who found complex interactions between competencies and motivational aspects and, thus, argued that test performance was far more than just intelligence plus prior knowledge. Additionally, they found that attendance in advanced courses influenced students' performances on competence tests positively, which aligns with our results.
For further interpretations of the direct relationship between CPS and interest, in-depth analyses are necessary. Furthermore, our model has to be validated with a much greater sample size to improve parameter estimations. It would also be interesting to administer the chemistry-specific CPS task to different age groups in order to obtain information on the model fit across subgroups.
As a conclusion, CPS can be regarded as a construct which is predicted by covariates such as prior knowledge, intelligence, computer familiarity, course attendance, and their interconnections. Consequently, educational practitioners, who develop intervention programs in order to improve the students' CPS competencies, should take prior knowledge and personality characteristics, but also CPS competency as a separate ability into account.

References

Bryan, R. R., Glynn, S. M., & Kittleson, J. M. (2011). Motivation, achievement, and advanced placement intent of High School students learning science. *Science Education 95*, 1049-1065.

Bühner, M., Kröner, S., & Ziegler, M. (2008). Working memory, visual-spatial-intelligence and their relationship to problem-solving. *Intelligence, 36,* 672-680.

Cartrette, D. P., & Bodner, G. M. (2010). Non-mathematical problem solving in organic chemistry. *Journal of Research in Science Teaching, 47* (6), 643-660.

Funke, J. (2010). Complex problem solving: a case for complex cognition? *Cognitive Processing, 11,* 133-142.

Funke, J., & Frensch, P. A. (2007). Complex problem solving: The European Perspective – 10 years after. In D. Jonassen (Ed.), *Learning to solve complex scientific problems* (pp. 25-47). New York/London: Lawrence Erlbaum.

Greiff, S., & Funke, J. (2009). Measuring complex problem solving: The MicroDYN approach. In F. Scheuermann (Ed.), *The transition to computer-based assessment – Lessons learned from large-scale surveys and implica-*

tions for testing (pp. 157-163). Luxembourg: Office for Official Publications of the European Communities.

Hambrick, D. Z. (2005). The role of domain knowledge in higher-level cognition. In A. Engle, & O. Wilhelm (Eds.), *Handbook of Understanding and Measuring Intelligence* (pp. 361-372). , Thousand Oaks, CA: Sage.

Heller, K. A., & Perleth, C. (2000). *Kognitiver Fähigkeitstest für 4.-12. Klassen, Revision (KFT 4-12+R) [Cognitive ability test for grades 4 to 12, Revision (KFT 4-12+R)]*. Göttingen: Hogrefe.

Kalyuga, S. (2006). Instructional and testing for expertise: A cognitive load perspective. In A. M. Columbus (Ed.), *Advances in Psychology Research* (Vol. 46, pp. 75-127). New York: Nova Science Publishers.

Koeppen, K., Hartig, J., Klieme, E., & Leutner, D. (2008). Current issues in competence modeling and assessement. *Journal of Psychology, 216* (2), 61-73.

Köller, O., Trautwein, U., Lüdtke, O., & Baumert, J. (2006). Zum Zusammenspiel von schulischer Leistung, Selbstkonzept und Interesse in der gymnasialen Oberstufe [About the relationships between performance, self-concept, and interest within the upper secondary level]. *Zeitschrift für Pädagogische Psychologie, 20* (1/2), 27-39.

Koppelt, J. (2011). *Modellierung dynamischer Problemlösekompetenz im Chemieunterricht* [Modeling complex problem solving competencies in chemistry]. Doctoral dissertation, Humboldt-Universität zu Berlin, Berlin, Germany.

Lee, K.-W. L., Goh, N.-K., Chia, L.-S., & Chin, C. (1996). Cognitive variables in problem solving in chemistry: A revisited study. *Science Education, 80* (6), 691-710.

Leutner, D. (2002). The fuzzy relationship of intelligence and problem solving in computer simulations. *Computers in Human Behavior, 18,* 685-697.

Marsh, H. W., Hau, K.-T., & Grayson, D. (2005). Goodness of fit in structural equation models. In A. Maydeu-Olivares, & J. J. McArdle (Eds.), *Contemporary Psychometrics* (pp. 275-340). Mahwah, NJ: Lawrence Erlbaum.

Muthén, B. O., & Muthén, L. K. (2010). *Mplus 6* [Computer software]. Los Angeles: Muthén & Muthén.

OECD (2009). *PISA 2006 Technical report.* Paris: OECD.

OECD (2010, September). *PISA 2012 Field trial problem solving framework – Draft subject to possible revision after the field trial.* Available at http://www.oecd.org/dataoecd/8/42/46962005.pdf [2011-08-04].

Schoppek, W., & Putz-Osterloh, W. (2003). Individuelle Unterschiede und die Bearbeitung komplexer Probleme [Individual differences and complex problem solving]. *Zeitschrift für Differentielle und Diagnostische Psychologie, 24* (3), 163-173.

Schroeders, U., & Wilhelm, O. (2011). Computer usage questionnaire: Structure, correlates, and gender differences. *Computers in Human Behavior, 27,* 899-904.

Taasoobshirazi, G., & Glynn, S. M. (2009). College students solving chemistry problems: A theoretical model of expertise. *Journal of Research in Science Teaching, 46* (10), 1070-1089.

Wirth, J., & Klieme, E. (2004). Computer-based assessment of problem solving competence. *Assessment in Education: Principles, Policy and Practice, 10* (3), 329-345.

Wu, M. L., Adams, R., & Wilson, M. (2007). *ConQuest – Generalised item response modelling software, draft release 2* [Computer software]. Melbourne: Australian Council for Educational Research.